# Parametric Bootstrap Tests for Futures Price and Implied Volatility Biases With Application to Rating Dairy Margin Insurance

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**ABSTRACT**

**Parametric Bootstrap Tests for Futures Price and Implied Volatility Biases With Application to Rating Dairy Margin Insurance**

We develop a new parametric bootstrap-based statistical test for presence of futures price and options-based implied volatility biases. The new test is applicable to data with overlapping prediction horizons. Information on anticipated volatility embedded in options prices is explicitly used when testing for futures price biases. Our method is well adapted to analysis of fast-changing commodity markets as it does not rely on asymptotic theory and does not require a time series spanning several decades. We apply the new test to investigate if futures and options biases can explain very low loss ratios exhibited by USDA's Livestock Gross Margin for Dairy Cattle insurance program.

**Keywords:** parametric bootstrap, futures price bias, volatility bias, revenue insurance, LGM-Dairy

Parametric Bootstrap Tests for Futures Price and Implied Volatility Biases With Application to the Rating of Dairy Margin Insurance

Traditional crop insurance products supported by USDA have focused on protecting the farm operator from production risks. Crop revenue protection programs were first offered in 1998 and have enjoyed continually increasing adoption rates. More recently, a new generation of revenue protection products has been introduced to address the revenue insurance needs of cattle, swine and dairy producers. The focus of this article is on the Livestock Gross Margin for Dairy Cattle (LGM-Dairy) revenue insurance program. LGM-Dairy is designed to compensate participating dairy farm operators  for unexpected declines in their gross margin defined as the difference between milk revenue and purchased feed costs (Gould and Cabrera 2011; Gould 2012).

A key feature of all insurance products endorsed by the Federal Crop Insurance Corporation is the contract design rule that stipulates premiums, before subsidies, must be actuarially fair. Table 1 reveals that after five years of pilot-program status, LGM-Dairy has generated premium revenue that exceeds indemnity payments by close to fifteen to one. Given this historical record the assumption of actuarial fairness has been questioned with the suggestion that the LGM-Dairy insurance product may be substantially over-priced (Novakovic 2012).

[Insert Table 1 about Here]

What LGM-Dairy ratemaking assumptions could result in biased insurance premiums? Under LGM-Dairy expected margins are calculated by multiplying the insured quantity of milk marketed and declared livestock feed by futures prices at contract sign-up. The expected variance of the insured IOFC margin is based on implied volatilities extracted from at-the-money options using the Cox, Ross and Rubinstein (1979) option pricing method. The LGM-Dairy rating method assumes that futures prices are unbiased predictors of terminal prices and that options prices accurately reflect the magnitude of futures price risk. LGM-Dairy premiums are highly sensitive to the assumption of zero risk premiums in futures and option prices. If milk (corn or soybean meal) futures prices are downward (upward) biased, or if option-implied expected variances over-predict the true level of risk in milk or livestock feed markets, then LGM-Dairy premiums will be upward biased, potentially resulting in abnormally low loss ratios.

Should we expect to find price or volatility risk premiums embedded in futures and options prices? Futures prices will be unbiased predictors of realized prices only if they are efficient and embody zero risk premium. However, the efficient market hypothesis does not stipulate zero risk premium. To the contrary, finance theory predicts speculators will have to be rewarded for holding a futures position if that exposes them to systemic risk (Dusak, 1973). Likewise, variance estimates based on options-implied volatility will equal the second moment of the true price distribution only under a set of practically unattainable conditions needed for markets to be dynamically complete (Constantinides, Jackwerth and Perrakis, 2008). Transaction costs and jumps in futures prices prevent construction of a continuously adjusted risk-free portfolio that underpins all risk preference-free option pricing models. If a short option position exposes speculators to systemic risk, option prices will reflect the volatility risk premium.

The empirical evidence regarding biases in commodity futures and options markets is mixed. For example, while Kolb (1992), Deaves and Krinsky (1995), and McKenzie and Holt (2002) find risk premiums in futures prices for at least some commodities they examined, Frank and Garcia (2009) find no evidence of time-varying risk premiums in the markets they analyzed. Some researchers have found implied volatilities to be upward biased estimates of realized volatility (McKenzie, Thomsen, and Phelan, 2007; Brittain, Garcia and Irwin, 2011). Others find no evidence of volatility bias (Urcola and Irwin, 2011; Egelkraut, Garcia and Sherrick, 2007).

The purpose of this analysis is to determine if biases in futures prices or expected variances extracted from options can explain extraordinarily low loss ratios of LGM-Dairy insurance. The contribution of our research is the development and application of a new statistical method for testing futures price and option-based volatility unbiasedness assumptions. The new statistical method is warranted for two reasons. First, existing methods for testing biases in futures prices use only data from futures and spot prices (e.g. Beck 1994; McKenzie and Holt, 2002; Frank and Garcia, 2009). Heteroskedasticity and autocorrelation consistent (HAC) estimators such as those by Hanson and Hedrick (1980) or Newey and West (1987) utilize only realized prediction errors and their covariance. In contrast, our method explicitly uses the information on options-implied expected volatility. In our method, higher implied volatilities, ceteris paribus, increase the burden of evidence needed to reject the null hypothesis of no futures price bias.

Second, testing for biases at long horizons must address the overlapping data issue. In particular, shocks to futures prices at long horizons are likely to be very strongly correlated, as prediction horizons of consecutive futures contracts have significant overlap. Historically this problem is addressed by using a variety of heteroskedastic and autocorrelated error covariance structures (Hansen and Hodrick, 1980; Newey and West, 1987; Karali and Thurman, 2009). When a small sample size does not permit reliance on asymptotic theory, bootstrap methods have been used as an alternative to test for presence of futures price bias (e.g. Mark 1995). To our knowledge, bootstrap methods have not yet been applied in parametric tests for biases in volatility forecasts. The new method developed here allows for joint tests of futures price and volatility biases in small samples when observed data has strongly overlapping prediction horizons.

The remainder of the paper is organized as follows. We begin the analysis with a brief description of the LGM-Dairy insurance program. Focus is on assumptions regarding marginal distributions generated from futures and options data. In the third section we propose a new parametric bootstrap procedure to test whether or not observed futures and option price data are consistent with the LGM-Dairy rating method. Contrary to previous research, we find volatility forecasts for distant months extracted from Class III milk options to be *downward* biased. In the fourth section we argue how such a bias could emerge and persist in thin futures markets when the underlying commodity is continuously produced as is the case of milk. In the concluding section of this analysis we discuss the implications of our findings with respect to the current LGM-Dairy premium setting method.

**A Brief Overview of the LGM-Dairy Rating Method**

LGM-Dairy contracts can be purchased once a month after the Chicago Mercantile Exchange (CME) Group futures markets close on the last business Friday of each month. Only one LGM-Dairy contract can be purchased each month and a farmer may insure at most 10 months of gross margin under any one insurance contract, not including the first month after the sales date.

Let $t$ represent the month of LGM-Dairy contract purchase and $i$ the ranking of the insurable month, $i = 1,...,10.$ Expected milk revenues under LGM-Dairy are based on the three-day average of Class III futures settlement prices $f_{t,i}^{M}$ prior to and including the prices on the day the LGM-Dairy contract is purchased, multiplied by declared milk marketed $M_{t,i}$ in each of up to 10 insurable months. At sign-up, expected feed costs are based on the same previous three-day average of futures prices for corn $f_{t,i}^{C}$ and soybean meal $f_{t,i}^{SBM}$, multiplied by the declared corn $C_{t,i}$ and soybean meal $SBM_{t,i}$ equivalents expected to be purchased and fed over the coverage period. For those months for which corn or SBM futures are not traded, the associated prices are defined as the weighted average of the CME futures settlement prices obtained from surrounding months.[1]

In addition to monthly milk marketings and declared feed amounts, a farmer must decide on the Gross Margin Deductible, $D_t$, i.e., the threshold decline in expected gross margin for insured milk after which LGM-Dairy will begin paying indemnities. Given the decision on the quantity for milk marketings declared feed use and deductible level, the gross margin guarantee $G_t$ is calculated as:

(1)
$$G_t = \sum_{i=1}^{10}\left[\left(f_{t,i}^{M} - D\right)\times M_{t,i} - \left(f_{t,i}^{C}\times C_{t,i} + f_{t,i}^{SBM}\times SBM_{t,i}\right)\right]$$

The realized (i.e., actual) gross margin, $R_T$, is calculated as:

(2)
$$R_T = \sum_{i=1}^{10}\left[p_{T,i}^{M}\times M_{t,i} - \left(p_{T,i}^{C}\times C_{t,i} + p_{T,i}^{SBM}\times SBM_{t,i}\right)\right]$$

where $p_{T,i}^{M}$, $p_{T,i}^{C}$, $p_{T,i}^{S}$ are terminal milk, corn and soybean meal prices, respectively estimated as the average of the last three settlement prices prior to the last trading day of the underlying futures contract.

[1] For example, when purchasing an LGM-Dairy contract at the end of July, the expected October corn price is the weighted average of September and December corn futures prices where the weights are 0.667 and 0.333, respectively. This is not a problem for Class III milk as future contracts exist for all months.

The LGM-Dairy ratemaking is designed to be actuarially fair. To that end, contract-specific policy premiums $C_t$ ($/cwt) are set equal to expected indemnities[2]:

(3) $$C_t = E_t\left[\max(G_t - R_T, 0)\right]$$

The LGM-Dairy premiums are determined by simulating $R_T$ using Monte Carlo simulation methods. A joint conditional distribution of terminal prices is constructed based on information available at the time of contract purchase. With 10 insurable months and three commodities involved, the joint distribution of interest consists of 30 marginal distributions and a linear correlation matrix that ties them together. Of the 30 marginal distributions, up to 24 are obtained directly from options and futures data, and the rest are interpolated through weighted averaging of surrounding marginal distributions. The marginal distributions of milk and feed prices are joined together through the Iman-Conover (1982) procedure equivalent to the Gaussian copula method (Mindenhall 2006). The LGM-Dairy premium is estimated as the simple average (plus 3%) of 5,000 simulated indemnities based on the assumed joint log-normal price distribution (RMA, 2005).

The focus of this article is on the assumptions regarding the marginal distributions, which we now list and discuss in detail. First, it is assumed that all marginal price distributions are lognormal. This assumption is not likely to be valid for annually harvested storable commodities. Due to non-negativity constraints on commodity inventories, commodity prices dynamics exhibit occasional sharp price spikes. Precipitous drops of the similar magnitude are not as likely. Thus, the resulting conditional price distributions are likely to have skewness levels higher than that

[2] Full insurance costs include administrative and overhead fees, as well as 3% surcharge paid to the Federal Crop Insurance Corporation.

which is consistent with assumed lognormality (Deaton and Laroque, 1992; Geman, 2005; Pirrong, 2011, Bozic and Fortenbery, 2011).

A random variable with a lognormal distribution is fully characterized by its first two moments. Futures prices determine the first moment. The LGM-Dairy rating method assumes futures prices are unbiased predictors of terminal prices. As emphasized in the introduction, this assumption is rather restrictive, as it requires futures prices to be not only efficient, but also to carry no marginal risk premium.

The stochastic process for futures prices consistent with terminal price lognormality is the geometric Brownian motion (GBM). That process underpins the Black's option pricing model (Black, 1976). When option contracts allow for early exercise, the Cox, Ross and Rubinstein (1979) (CRR) binomial option pricing model can be used. When option sellers can offset the risk of holding a short option position without transaction costs by assuming a continuously adjusted position in the underlying futures contract, the markets are said to be dynamically complete (Constantinides, Jackwerth and Perrakis, 2008). Under these conditions, option contract premiums are the expected value of the option payoff under a risk-neutral distribution. Inverting the process, expected risk-neutral variance can be extracted from the option prices. When markets are dynamically complete, and the underlying asset follows a geometric Brownian motion, the risk-neutral and true futures price distribution will have the same variance. LGM-Dairy premium determination utilizes the CRR method to extract implied volatility from at-the-money option prices.

Incorporating the above LGM-Dairy rate making assumptions, the conditional marginal distribution $\psi_t(\cdot)$ of the terminal log-price $\ln p_T$ is

(4) $$\psi_t(\ln p_T; f_t, \sigma_t) \sim N\left(\ln f_t - \frac{1}{2}\sigma_t \tau, \sigma_t^2 \tau\right)$$

where $T$ is the expiration date, $\tau \equiv \frac{T-t}{252}$ annualized time to expiration, futures price is denoted $f_t$ and implied volatility is $\sigma_t$.

There are at least two reasons why variance $\sigma_t^2\tau$ built off CRR implied volatility may be biased. First, when the GBM assumption is violated, higher moments of the risk-neutral distribution may differ from those of the true price distribution. Second, common transaction costs such as trading fees and bid-ask spreads suffice to render markets imperfect and dynamic completeness unattainable. In such a scenario, option prices will reflect risk preferences of option sellers, who may require a risk premium to hold a short option position.

Finally, LGM-Dairy data collection methods embed some assumptions that also need to be discussed. Under the LGM-Dairy rating method, there are three alterations to observed futures and options data. First, instead of using a daily settlement futures prices on a particular day, expected prices are calculated by taking three-day averages of daily settlement futures prices. The same procedure applies for terminal prices.  Implied volatilities used in LGM-Dairy premium determination are similarly obtained but this using two-day averaging. Second, missing observations for implied volatilities at distant months are imputed using observed implied volatilities for contracts with shorter time-to-maturity. Finally, while corn and soybean meal options expire several weeks before their underlying futures contracts, for LGM-Dairy premium determination purposes, time-to-maturity is based on futures, rather than options expiration date.

Each of these alterations may be challenged. For example, if futures are efficient and unbiased, the last observed futures price is the most accurate forecast of the terminal price. Three-day average of futures prices would then introduce a bias whenever prices of the previous two days do not correspond to the last used futures price. A similar argument can be made concerning the averaging implied volatilities. Finally, imputing missing implied volatilities by adjusting for time-to-maturity is only appropriate when underlying cash price series contains a unit root. If the underlying commodity cash prices are mean-reverting then imputed volatilities are likely to be upward biased.

**Parametric Bootstrap Tests of Unbiasedness in Futures Prices and Implied Volatilities**

The LGM-Dairy marginal price distribution assumptions could be considered to be relatively strong. Are observed prices consistent with these assumptions? In this section we develop a method for generating simulated terminal prices with the data generating process (DGP) consistent with the LGM-Dairy assumptions. We then test how likely the observed prices are given the assumed DGP. It is important to emphasize that we are not designing the new procedure to test any particular economic theory. In many applied works testing market efficiency, it is critical to design a model in such a way to differentiate between futures prices biases emerging from risk premium vs. biases that are result of informational inefficiencies (McKenzie and Holt, 2002; Frank and Garcia, 2009). In contrast, our objective is to examine if LGM-Dairy insurance is likely to be under- or overpriced due to the assumptions of the rating method. As such, it is more important to know the direction and magnitude of a price bias than to decompose its source.

The composite hypothesis we seek to test is given in (4). It is a joint test of lognormality, unbiasedness of futures prices and unbiasedness of option prices. We split (4) into two testable hypotheses:

**H1**: Futures prices are unbiased predictors of terminal prices

**H2**: Squared implied volatilities multiplied by time left to maturity are an unbiased predictors of terminal log-price variances.

If either **H1** or **H2** is rejected, the composite hypothesis represented by (4) is rejected. Under **H1** we have

(5) $$f_{t,i} = E_t\left(p_{T,i}\right)$$

where $p_{T,i}$ is the terminal price for the $i^{th}$ insurable month. To standardize, we divide (5) by $f_{t,i}$, and obtain

(6) $$E_t\left(\frac{f_{t,i} - p_{T,i}}{f_{t,i}}\right) = 0$$

From (6) the percentage prediction error (PPE) is defined as:

(7) $$PPE_{t,i} \equiv \frac{f_{t,i} - p_{T,i}}{f_{t,i}} \times 100$$

Over $N$ contracts with unbiased futures prices, we would expect the average PPE to be close to zero. Therefore, an appropriate sample equivalent of equation (7) is

(8) $$\overline{PPE}_i = \frac{1}{N}\sum_{l=1}^{N}\frac{f_{l,i} - p_{l,i}}{f_{l,i}} \times 100 = \frac{1}{N}\sum_{l=1}^{N} PPE_{l,i} = 0$$

where $f_{l,i}$ is the three-day average futures price for contract $l = 1,...,N$ observed at a time when it would have been used in a LGM-Dairy premium calculation as an expected price for $i^{th}$ insurable month. Terminal price is denoted $p_{l,i}$.

If **H2** is true then

(9) $$E_t\left(\sigma_{t,i}^2\tau - \left(\ln p_{T,i} - \left(\ln f_{t,i} - \frac{1}{2}\sigma_{t,i}^2\tau\right)\right)^2\right) = 0$$

Dividing (9) by the conditional variance of terminal log-prices $\sigma_{t,i}^2\tau$ we obtain

(10) $$E_t\left[\frac{\ln p_{T,i} - \left(\ln f_{t,i} - \frac{1}{2}\sigma_{t,i}^2\tau\right)}{\sigma_{t,i}\sqrt{\tau}}\right]^2 = 1$$

We denote the expression in the brackets as the squared standardized prediction error (SSPE). Over $N$ contracts with unbiased futures prices as well as unbiased implied volatilities, we would expect SPPEs to average to one. We can calculate root mean square standardized prediction error (RMSSPE) as:

$$RMSSPE_i = \sqrt{\frac{1}{N}\sum_{l=1}^{N}\left[\frac{\ln p_{l,i} - \left(\ln f_{l,i} - \frac{1}{2}\sigma_{l,i}^2\tau\right)}{\sigma_{l,i}\sqrt{\tau}}\right]^2} \tag{11}$$

The testable implication of **H2** is:

$$\sqrt{\frac{1}{N}\sum_{l=1}^{N}\left[\frac{\ln p_{l,i} - \left(\ln f_{l,i} - \frac{1}{2}\sigma_{l,i}^2\tau\right)}{\sigma_{l,i}\sqrt{\tau}}\right]^2} \stackrel{?}{=} 1 \tag{12}$$

Since the time of futures price measurement falls before all previous contracts have expired prediction percentage errors $PPE_{t,i}$ as well as $SSPE_{t,i}$ will be autocorrelated. For distant horizons, these autocorrelations may be rather strong. As an example, consider Class III milk prices for the 9$^{th}$ insurable month. The autocorrelation at first lag for $PPE_{t,9}$ is 0.906. If our bootstrapped distributions of test statistics $\overline{PPE}_i$ and $RMSSPE_i$ are to truly reflect the hypothesized data generating process we need to explicitly account for these autocorrelations.

In order to test **H1** and **H2**, subject to both correlated prediction errors and relatively small sample sizes, we proceed by utilizing our new parametric bootstrap approach to approximate the distribution of test statistics shown in equations (8), (12) under the DGP summarized by (4). We then test each hypothesis using bootstrapped p-values.

*Simulating Terminal Prices*

We will denote bootstrapped variables and statistics with an asterisk $(*)$ to differentiate them from observed data and sample-based statistics. For a given insurable month $i,$ we simulate terminal prices $p^{*}_{T,i}$ by:

$$p^{*}_{T,i} = \exp\left(z^{*}_{T,i} \times \sigma_{t,i}\sqrt{\tau} + \left(\ln f_{t,i} - 0.5 \times \sigma^{2}_{t,i}\tau\right)\right) \tag{13}$$

where $z^{*}_{T,i}$ are autocorrelated draws from a standard normal distribution. Autocorrelations in $z^{*}_{T,i}$ must be such that they reflect autocorrelations in $PPE_{t,i}$ and $SSPE_{t,i}$ as well as restrictions imposed by the null hypotheses **H1** and **H2**.

A general expression for an $ARMA(p,q)$ process is:

$$z_t = \sum_{m=1}^{p}\varphi_m z_{t-m} + \sum_{m=1}^{q}\alpha_m \varepsilon_{t-m} + \varepsilon_t \quad \varepsilon_t \sim N\left(0,\sigma^{2}_{\varepsilon}\right) \tag{14}$$

Both **H1** and **H2** will impose restrictions on ARMA coefficients in (14). Let $j$ be the highest nearby index of futures prices used in calculation of $i^{th}$ insurable month's expected prices under LGM-Dairy rating method. **H1** stipulates futures prices are unbiased. If futures prices are unbiased, they must be efficient. Under futures markets efficiency, for the $j^{th}$ nearby futures prices, autocorrelations in $PPE_{t,i}$ at lags higher than $j-1$ must be zero. If that were not the case, then observed past prediction errors could improve the forecasting power of futures prices. In order to achieve this condition, the number of autoregressive lags for $z_t$ draws must be set to zero, and only up to $j-1$ moving average lags can be allowed. In other words, from **H1** it follows that $ARMA(p,q)$ in equation (14) must be restricted such that $p=0, q<j.$

**H2** stipulates $Var_t\left(\ln p_T\right) = \sigma^{2}_{t,T}\tau$ . From (13), it follows that

(15) $$Var_t\left(\ln p^*_{T,i}\right) = \sigma^2_{t,i}\tau \times Var_t\left(z^*_{T,i}\right)$$

The conditional variance of $z^*_{T,i}$ must be equal to one. From (14) and restrictions imposed on (14) by **H1**, it follows that unitary conditional variance will only be achieved when

(16) $$\sigma^2_\varepsilon = \frac{1}{1+\sum_{m=1}^{j-1}\alpha^2_m}$$

The final issue to be resolved regards the estimation of moving average coefficients in (14). In order to do that, we use information on realized shocks to construct observed $z_{T,i}$ scores and fit $MA\left(j-1\right)$ models. Using the cumulative density function of terminal log-prices, conditional on information available at time *t*, $\Psi_t\left(.\right)$ with parameters $\ln f_{t,i} - 0.5\times\sigma^2_{t,i}\tau, \sigma^2_{t,i}\tau$, we can calculate the quantile $u_{t,i}$ of the realized terminal log-price $\ln p_{T,i}$

(17) $$u_{t,i} = \Psi_t\left(\ln p_{T,i}; \ln f_{t,i} - \frac{1}{2}\sigma^2_{t,i}\tau, \sigma^2_{t,i}\tau\right)$$

Under the null hypotheses, the implied quantile $u_{t,i}$ tells us where realized price falls in the time-*t* conditional distribution that is based on futures price and implied volatility. For example, if the implied quantile is 0.9 this implies that realized price is quite higher than expected at time *t*, i.e., the chance of the terminal price settling at that particular level or higher were deemed to be only 10%.

Berkowitz (2001) used the inverse probability integral transform to convert implied quantiles to draws from standard normal distribution. We follow a similar approach here and construct a series of standard normal z-scores based on quantiles $u_{t,i}$. The first step is to use the standard normal distribution function and inverse probability integral transform:

(18) $$\tilde{z}_{t,i} = \Phi^{-1}\left(u_{t,i}\right)$$

We must also account for the possibility that unbiasedness of futures-implied mean and options-implied variance may not actually be valid assumptions for the terminal price conditional distribution. Consequently, quantiles $u_{t,i}$, which are distributed uniformly under the null, may not be distributed uniformly in our sample. In order to capture the autocorrelation structure under the null hypotheses **H1** and **H2**, unrestricted z-scores $\tilde{z}_{t,i}$ are standardized to insure zero mean and standard deviation of one. Denote the mean and standard deviation of unrestricted z-scores $\tilde{z}_{t,i}$ as $\tilde{\mu}_i$ and $\tilde{\sigma}_i$, respectively. Restricted z-scores are then calculated as

$$z_{t,i} = \frac{\tilde{z}_{t,i} - \tilde{\mu}_i}{\tilde{\sigma}_i} \tag{19}$$

We use $z_{t,i}$ to fit coefficients of a $MA(j-1)$ model. Following equation (14) we then simulate z-scores via $z^*_{T,i} = \varepsilon_t + \sum_{m=1}^{j-1} \hat{\alpha}_m \varepsilon_{t-m}$. For each bootstrapped sample of z-scores, we run the $z^*_{T,i}$ series for 500 time periods before recording a sequence of length N. In total, $K$ samples of $N \times 1$ vectors of z-scores are simulated. Using **Error! Reference source not found.** we generate $K$ bootstrapped $N \times 1$ vectors of simulated terminal prices, denoted $p^*_{l,i}(k)$, $l = 1,...,N$ and $k = 1,...,K$.

*Determining Critical Test Statistic Values*

For each of the *K* bootstrapped samples of simulated terminal prices we calculate average PPE, denoted $\overline{PPE}^*_i(k)$ as

$$\overline{PPE}^*_i(k) = \frac{1}{N}\sum_{l=1}^{N} PPE^*_{l,i}, \quad k = 1,...,K \tag{20}$$

The formal tests of the futures unbiasedness hypotheses consists of constructing bootstrapped confidence intervals for the $\overline{PPE}^*_i(k)$ statistics and determining if the sample-data based $\overline{PPE}_i$

value lies within the critical region. The bootstrapped confidence interval with the probability of Type I error of $\alpha$ is found by sorting the bootstrapped $\overline{PPE}_i^*(k)$ statistics and identifying the critical values as entries at positions $\frac{\alpha}{2}K$ and $\left(1-\frac{\alpha}{2}\right)K$.

For this analysis we set the number of replications as $K = 20,000$ and $\alpha = 0.05$ so the critical values of the bootstrapped distribution are found at positions 500 and 19,500. If the sample $\overline{PPE}_i$ is lower than $\overline{PPE}^*_{j,\alpha/2}$ or higher than $\overline{PPE}^*_{j,1-\alpha/2}$ we reject the null hypothesis of unbiasedness of futures prices for $i^{th}$ insurable month. The advantage of our test over other approaches based on heteroskedasticity and autocorrelation consistent (HAC) estimators such as those by Hanson and Hedrick (1980) or Newey and West (1987) is that we utilize explicitly the information on expected volatility, while HAC estimators only use realized prediction errors and their covariance. Higher implied volatility coefficients will result in a more dispersed bootstrapped distribution of mean prediction percentage errors. Consequently, critical points $\overline{PPE}^*_{j,\alpha/2}$ and $\overline{PPE}^*_{j,1-\alpha/2}$ will be larger in magnitude. This larger value implies a higher burden of evidence needed to reject the null hypothesis of unbiased futures prices. In the online Appendix A we quantify in detail how much extra burden the overlapping nature of our data places on the evidence needed to reject the null hypothesis of no volatility bias.

For the volatility unbiasedness test (**H2**) we use bootstrapped root mean standardized square prediction errors, $RMSSPE_i^*(k)$. From (12) and (13), the square root of average bootstrapped SSPE can be simplified to:

$$RMSSPE^*(k) = \sqrt{\frac{1}{N}\sum_{l=1}^{N}\left(z^*_{l,k}\right)^2}, k = 1,\ldots,K \qquad (21)$$

Therefore, the bootstrapped distribution of the variance unbiasedness test statistic in (21) depends directly on the autocorrelation structure of standard normal draws $z_{l,k}$ and sample size, but not on futures prices or implied volatilities.

*Description of Data Used in the Analysis*

We apply the above bootstrap procedures to a set of Class III milk futures and options contracts from January 2000 through August 2013. Class III milk futures and options are traded for all twelve calendar months, so our sample period yields 164 observations. For corn and soybean meal, sample period encompasses contracts from January 2000 through September 2013. Corn futures trade for five calendar months (March, May, July, September and December) and soybean meal futures trade for eight calendar months (January, March, May, July, August, September, October and December). The total numbers of monthly observations for these commodities are 69 and 110, respectively.

To obtain the data series we use in our tests we construct a sequence of expected and terminal prices and two-day average implied volatilities for $i^{\text{th}}$ insurable month, where $i = 1,\ldots,10.$ As the LGM-Dairy contract allows insurance to cover up to ten months, each futures/options contract month is used for price discovery purposes at ten consecutive LGM-Dairy sales events. Therefore, for each futures/options contract month we collect data at ten time-to-maturity horizons, corresponding to periods where futures and options data from this contract month would be used as LGM-Dairy information sources. Descriptive statistics are presented in Table 2.

[Insert Table 2 about Here]

*Results of the Parametric Bootstrap Tests*

The results of our parametric bootstrap tests for unbiasedness of futures prices are summarized in Table 3. Average PPE's for Class III milk and corn are rather small, and fall well within the 95% bootstrapped confidence interval. For soybean meal futures, mean PPE's are negative and larger for more distant insurable months. Expected soybean meal prices, as defined by the LGM-Dairy rating rules, have been on average 10.24% below the terminal price for the 6$^{th}$ insurable month, and 15.41% below the terminal price for the 10$^{th}$ insurable month. For this commodity, mean prediction errors lie outside the 95% confidence interval for all insurable months, and p-values are less than 0.01. We conclude that Class III and corn futures prices are unbiased predictors of terminal futures price at all prediction horizons examined. In contrast, soybean meal prices exhibit statistically significant and substantial downward bias.

[Insert Table 3 about Here]

Results of our bootstrap tests for implied volatilities are given in Table 4. RMSSPEs for corn lie well within the 95% confidence interval. For soybean meal and Class III milk, the null hypothesis of no volatility bias is rejected. Given the earlier finding of bias in soybean meal futures prices, we must be careful in interpreting the results of either futures price or volatility bias tests. If futures prices are indeed biased, but bias is due solely to time-varying risk premium and not informational inefficiencies, then the test for volatility biases based on equations **Error! Reference source not found.** and **Error! Reference source not found.** will be misspecified. To check for robustness of our results in the online Appendix B we develop a version of the volatility bias test that can accommodate time-varying risk premiums in futures prices. We show that under that model specification, the null hypothesis of no volatility bias in soybean meal options is not rejected. The most robust conclusion is not, however, that soybean meal futures contain a risk-premium. The proper conclusion is that that the parametric bootstrap tests reject the composite null hypothesis (4) of no bias in either soybean meal futures prices or implied volatilities.

Implied volatility unbiasedness is rejected for Class III milk options for all insurable months. Before analyzing the potential causes of this bias, another robustness check is in order. In particular, we need to examine if this result could be attributed to alterations of futures and options data stipulated in the LGM-Dairy rating method as described in the second section of this article. The results of this robustness test are discussed in detail in the online appendix C. The short conclusion is that the stated alterations do not seem to qualitatively change the parametric bootstrap test results.

**Analysis of Class III Milk Implied Volatility Biases**

The direction of the Class III milk implied volatility biases stands in clear contradiction to the previous literature (McKenzie, Thomsen and Phelan, 2007; Brittan, Garcia and Irwin, 2011; Bodarenko, 2004, Gabaix, 2012). In other commodities, when implied volatilities have been determined to be biased, upward bias has been identified, i.e., implied volatilities were higher than the realized volatility. In contrast, results of our tests suggest that implied volatilities have actually been under-predicting the magnitude of risk in Class III futures markets.

From the magnitude of RMSSPEs it is not clear as to whether these results are also economically important. To examine the issue further we create a long straddle-based trading strategy that would generate zero profits if implied volatilities are unbiased, but would yield positive profits if implied volatilities are too low relative to realized shocks. Even after accounting for typical slippage, returns over the past 13 years average 27%. Therefore, the results from our trading exercise not only corroborate parametric bootstrap results, but suggest that returns on strategies exploiting apparent volatility bias in Class III options are considerably high. Online Appendix D discusses the trading program analysis in further detail.

One explanation often invoked to explain asset returns puzzles is the effect of rare large disasters on *ex ante* returns (Gabaix 2012). As Lewis (2008) explains, because asset prices are determined by expectations about the paths of future economic variables, they will reflect expectations about infrequent discrete shifts in economic determinants. Consequently, the rational forecast errors may have a mean different from zero in finite samples, as observed data in any given sample would reflect expectations for a rare event that could have plausibly happened, but did not happen in the sample (Bodarenko 2004).

If a sample does not contain the rare event that is nevertheless factored in the put option premiums, then *ex post* returns to selling puts may seem high. Apparent mispricing is thus a small sample issue, and would vanish with a sufficiently large sample containing the rare event at its true relative frequency. While the literature is mostly concerned with samples which do not include anticipated rare events, the logic may be extended to small samples around the rare event that actually did occur. In such a scenario, options may indeed seem underpriced, as positive returns to long option positions at event time may dominate the sample. This conjecture points to a likely a violation of the lognormality assumption. Lognormal distribution has thin tails. Under alternative distributional assumptions, an extreme tail event might have been deemed much more likely, and a realization of such an event might not be judged by the parametric bootstrap test as radical departure from the model assumptions.

The most likely candidate for an over-represented rare event is the Great Recession of 2009, when prices of milk futures nearly halved. History indicates such major recessions occur once in half a century, not once in 13 years, which is the length of our sample. To examine this conjecture, we rerun the parametric bootstrap tests and trading programs with the truncated sample from which most likely rare events have been excluded. The results indicate presence of rare events may have contributed to high observed returns to long straddle positions, but the potential overrepresentation of rare events does not fully explain the apparent downward bias in Class III milk implied volatilities, especially for prediction horizons from 120 to 220 calendar days to maturity. For details consult the online Appendix E.

If the mispricing is not a result of discrepancy between *ex ante* and *ex post* returns induced by rare events, then an explanation must be offered why this trading opportunity has not yet been exploited by speculators. We presented the results of our straddle trading strategy discussed above to seven commodity traders at the CME Group. Those employed at large trading companies that regularly speculate or hedge in many commodity markets found dairy option markets to be too small and illiquid to justify their engagement. Dairy option markets for horizons longer than four months are particularly thin, and in their opinion even a very modest speculative activity would suffice to significantly raise distant month options premiums, thus closing this trading opportunity. In addition, this investment opportunity is not only small in absolute sense, but based on historical record, it would also necessitate dedicated trading program spanning at least 36 trades/months before meaningful profits can be expected with reasonably high probability. For that reason, and given the uncertainty regarding future dairy policy, traders in companies specializing in dairy risk management found the necessary commitment horizon too long to spur investment interest.

Barely existent trading activity may be able to explain the persistence of biased option prices. But we must still explain why option prices emerged to be too low, rather than too high.

The rare events hypothesis is a plausible partial explanation, but it is our conjecture that price-forming heuristics, structure of trades and distribution of liquidity across trading months all contribute to the direction of the volatility bias. A significant percentage of Class III trading activity occurs in the front three months. At contract expiry, Class III futures market cash settles against USDA announced Class III milk price based on four/five-week average cheese, dry whey and butter prices. As such, volatility of futures prices in the last thirty trading days dramatically decreases. Consequently, daily settlement option prices for the first three nearby contracts typically have distinct implied volatilities increasing with time-to-maturity, indicating an active option price discovery process. In contrast, the implied volatility term structure is typically flat for $4^{th}$ and higher nearby contracts. In our conversations with dairy option market makers, it was their opinion that implied volatilities for $3^{rd}$ or $4^{th}$ nearby month are used as a natural starting point in forming prices for options for more distant months, with premiums adjusted for longer time-to-maturity. Therefore, trader's heuristics regarding the thin segment of the market (distant contract months) may contribute to the apparent volatility biases.

Given the continuous nature of milk production, it is very common for a producer to buy option 'packs' traded as bundles covering a minimum of three, and often more months. A "pack" of options is defined by a common strike, and quoted with a single price. When prices are recorded for official purposes, they are split for individual months by assuming an average implied volatility for the entire period covered by the pack. The practice of buying options as 'packs' with overlapping periods, rather than individual contracts, is more prevalent for distant months, and may further mute the option price discovery process beyond the $3^{rd}$ nearby contract.

In conclusion, high trading activity in front months encourages an active price discovery process, and implied volatilities that emerge for the $3^{rd}$ nearby contract are likely used by option sellers as a starting point in pricing options for more distant months. If the variance of prices grows faster with time-to-maturity than is implied by flat volatility term structure with volatility coefficient based on 3rd nearby contract, then flat volatility curve would indeed induce downward biased option prices. Finally, low speculative and hedging demand, and the common practice of hedging via use of option ‘packs’ jointly mute option price discovery at more distant months, allowing downward bias in implied volatilities to persist.

## Conclusions

In this analysis we have developed a novel method for testing for presence of futures price and implied volatility biases. Our method is suitable for short sample periods and data with overlapping forecast horizons. Existing methods, such as Hansen-Hodrick and Newey-West estimators, rely on residuals standard error to form autocorrelation-consistent confidence intervals of futures prediction errors. As such, these methods use only information on realized variance of futures prices. Our parametric bootstrap test improves upon existing methods by utilizing available information on anticipated volatility, which we infer from option prices. Furthermore, to our knowledge, ours is the first empirical analysis to properly account for residual autocorrelated errors when testing for presence of bias in implied volatility coefficients.

We applied our method to evaluate actuarial assumptions used in premium determination of the Livestock Gross Margin Insurance for Dairy Cattle. We find Class III milk and corn futures prices to be unbiased. The composite hypothesis of no futures price and implied volatility biases is rejected for soybean meal. Without additional assumptions regarding risk premiums in soybean meal futures it is not possible to determine if the hypothesis is rejected due to futures prices or implied volatility biases.

Tests for the presence of bias in implied volatility coefficients suggest that milk options exhibit downward bias. This result stands in stark contrast to financial literature that regularly finds options prices to be over- rather than underpriced (McKenzie, Thomsen and Phelan 2007; Brittan, Garcia and Irwin 2011; Bodarenko 2004; Gabaix 2012). After accounting for possibly over-represented rare events that induced major milk price shocks, we still find Class III options underestimating the futures price volatility for contracts with 5 to 10 months to maturity. Possible reasons for emergence of downward bias in Class III options include (i) heuristics used by market makers to form prices for thin and illiquid distant Class III options, (ii) the prevalent practice of purchasing of Class III options in 'packs' rather than individual contract months which mutes option price discovery process. Market thinness, policy uncertainty, and the length of commitment necessary to guarantee high profits with reasonably high probability jointly explain why these biases can persist despite possibly highly lucrative trading programs that can be devised to exploit options mispricing.

Although LGM-Dairy is a government-sponsored margin insurance product with a transparent rating method and explicitly designated to be actuarially fair, large underwriter gains over the past 4 years have led some to question the soundness and robustness of the official rating method. Based on our parametric bootstrap tests and simulation experiments, our conclusion is that assumptions regarding marginal distributions of milk and feed prices do not produce insurance premiums that could be considered excessive. On the contrary, correcting for identified downward biases in soybean meal futures and/or option prices and Class III milk options prices would increase, rather than decrease LGM-Dairy premiums. For detailed analysis consult the online Appendix F. Given that the previous work (e.g. McKenzie and Holt 2002; Frank and Garcia 2009; Gorton, Hayashi and Rouwenhorst 2012) does not find biases in soybean meal futures prices, it would be our recommendation that further research be done to understand the origin and persistence of bias in soybean meal prices that emerged in the last decade. If further work corroborates our results, our recommendation to the LGM-Dairy contract designers would be to use a conservative approach whereby expected prices are adjusted for bias when calculating gross margin guarantees. Such an approach would reduce the gross margin guarantee without substantially altering the premiums compared to the current method.

Based on this work, our recommendation is that in pricing LGM-Dairy insurance, Class III milk option biases be corrected using a conservative method that excludes possibly overrepresented rare events when calibrating implied volatility to account for the uncovered volatility biases. If option markets continue to exhibit strong downward volatility bias over the forthcoming decade, the rare-events explanation would further lose credibility, and premiums should then be adjusted using the calibration based on full data sample.

If the futures and options biases cannot explain the low LGM-Dairy loss ratios, an explanation for a possible insurance premium bias must be sought elsewhere. XXX et al. (2013) [REFERENCE WITHHELD FOR REVIEW PURPOSES] examined if accounting for non-lognormal skewness and kurtosis may provide an answer and found the LGM-Dairy premiums robust to violations of lognormality assumption. XXX et al. (2013b) [REFERENCE WITHHELD FOR REVIEW PURPOSES] find the LGM-Dairy premiums highly sensitive to assumptions regarding the strength and nature of dependence between milk and feed prices. XXX et al. (2013b) demonstrate that correcting the LGM-Dairy rating method to account for expected co-movements between milk and feed prices results in long-run LGM-Dairy loss ratios close to one.

Parametric bootstrap methods for examining biases in futures and options prices can be further improved by relaxing the assumptions regarding stochastic process for underlying futures prices. In particular, Bozic and Fortenbery (2011) confirm that futures prices in storable agricultural commodities exhibit skewness and kurtosis that are higher than consistent with lognormality. As such, parametric methods that utilize information from option prices across all traded strikes would be an improvement over our method employed in this article that follows LGM-Dairy rating method in using only at-the-money options. While our parametric bootstrap method was developed with a concrete purpose of testing actuarial assumptions of LGM-Dairy, its relevance is by no means restricted to our particular application. With commodity markets rapidly changing over the past decade, the parametric bootstrap methods for testing for presence of futures price biases should be preferred to methods that rely on asymptotic theory, require samples spanning several decades and ignore information on anticipated volatility embedded in the options prices.

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Table 1. LGM-Dairy Insurance Statistics Crop Insurance years 2009-2012

| Insurance Year | Policies Sold | Milk Marketings Insured | Gross Margin Guarantee | Premium | Indemnities Paid | Loss Ratio |
|---|---|---|---|---|---|---|
| | (No.) | (cwt) | ($) | ($) | ($) | |
| 08-09 | 40 | 401,680 | 4,715,858 | 287,201 | 718,035 | 2.50 |
| 09-10 | 134 | 1,872,499 | 24,914,997 | 781,589 | 280,566 | 0.36 |
| 10-11 | 1,224 | 46,172,815 | 769,644,504 | 25,012,757 | 64,738 | <0.01 |
| 11-12 | 898 | 40,504,408 | 704,520,655 | 19,153,150 | 1,317,954 | 0.07 |
| 12-13 | 687 | 34,188,752 | 664,253,548 | 16,878,326 | 1,737,692 | 0.10 |
| 13-14 | 150 | 4,470,452 | 81,639,835 | 1,572,438 | 0 | 0.00 |

Source: Risk Management Agency, http://www3.rma.usda.gov/apps/sob/ . Accessed Sept. 30, 2013.

Note: The contracts issued during 2012-13 and 2013-14 reinsurance years may not have matured as of Sept. 30, 2013.

Table 2. Descriptive Statistics for Data Used in Parametric Bootstrap

| Commodity/ LGM-Dairy Insurable Month | | Time to Maturity (Calendar Days) | | | Futures ($) | | | | Implied Volatility | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Avg | Min | Max | Avg | S.D. | Min | Max | Mean | S.D. | Min | Max |
| Class III Milk | | | | | | | | | | | | |
| 1 | 164 | 64 | 59 | 75 | 14.13 | 3.01 | 9.39 | 20.80 | 0.19 | 0.05 | 0.08 | 0.37 |
| 2 | 164 | 95 | 87 | 103 | 14.14 | 2.80 | 9.78 | 20.71 | 0.21 | 0.04 | 0.10 | 0.37 |
| 3 | 164 | 125 | 116 | 137 | 14.12 | 2.65 | 9.80 | 20.72 | 0.21 | 0.04 | 0.11 | 0.35 |
| 4 | 164 | 156 | 150 | 166 | 14.10 | 2.51 | 9.82 | 20.33 | 0.20 | 0.04 | 0.11 | 0.30 |
| 5 | 164 | 186 | 178 | 194 | 14.09 | 2.41 | 9.84 | 20.15 | 0.20 | 0.03 | 0.11 | 0.30 |
| 6 | 164 | 216 | 213 | 229 | 14.04 | 2.33 | 9.90 | 20.10 | 0.20 | 0.03 | 0.11 | 0.29 |
| 7 | 164 | 247 | 241 | 257 | 13.99 | 2.27 | 9.97 | 19.68 | 0.20 | 0.03 | 0.11 | 0.30 |
| 8 | 164 | 277 | 270 | 285 | 13.94 | 2.20 | 10.51 | 19.42 | 0.19 | 0.03 | 0.10 | 0.32 |
| 9 | 164 | 308 | 304 | 320 | 13.88 | 2.18 | 10.61 | 19.47 | 0.19 | 0.03 | 0.10 | 0.30 |
| 10 | 156 | 338 | 332 | 348 | 13.92 | 2.17 | 10.71 | 19.61 | 0.19 | 0.03 | 0.08 | 0.31 |
| Corn | | | | | | | | | | | | |
| 1 | 69 | 45 | 32 | 48 | 3.75 | 1.82 | 1.80 | 7.91 | 0.30 | 0.08 | 0.16 | 0.56 |
| 2 | 69 | 77 | 67 | 87 | 3.76 | 1.79 | 1.96 | 7.60 | 0.30 | 0.08 | 0.16 | 0.47 |
| 3 | 69 | 107 | 95 | 116 | 3.76 | 1.80 | 1.88 | 8.07 | 0.29 | 0.08 | 0.16 | 0.47 |
| 4 | 69 | 137 | 123 | 146 | 3.74 | 1.75 | 1.92 | 7.86 | 0.29 | 0.08 | 0.16 | 0.47 |
| 5 | 69 | 168 | 151 | 175 | 3.73 | 1.72 | 2.07 | 7.80 | 0.28 | 0.08 | 0.16 | 0.47 |
| 6 | 69 | 198 | 186 | 209 | 3.74 | 1.70 | 2.00 | 8.08 | 0.29 | 0.08 | 0.16 | 0.47 |
| 7 | 69 | 229 | 214 | 237 | 3.68 | 1.66 | 2.04 | 7.81 | 0.27 | 0.07 | 0.16 | 0.44 |
| 8 | 69 | 259 | 242 | 271 | 3.72 | 1.69 | 2.08 | 8.01 | 0.28 | 0.07 | 0.17 | 0.46 |
| 9 | 69 | 290 | 277 | 300 | 3.67 | 1.59 | 2.12 | 7.75 | 0.27 | 0.06 | 0.18 | 0.42 |
| 10 | 69 | 319 | 305 | 322 | 3.70 | 1.64 | 2.15 | 8.05 | 0.27 | 0.06 | 0.19 | 0.42 |
| Soybean Meal | | | | | | | | | | | | |
| 1 | 110 | 46 | 32 | 55 | 257.7 | 96.8 | 145.0 | 536.3 | 0.27 | 0.08 | 0.15 | 0.48 |
| 2 | 110 | 77 | 67 | 87 | 254.2 | 93.2 | 143.6 | 482.5 | 0.27 | 0.07 | 0.16 | 0.45 |
| 3 | 110 | 107 | 95 | 116 | 250.6 | 91.4 | 143.7 | 532.9 | 0.26 | 0.07 | 0.15 | 0.43 |
| 4 | 110 | 137 | 123 | 146 | 247.7 | 90.3 | 143.3 | 525.6 | 0.26 | 0.06 | 0.15 | 0.43 |
| 5 | 110 | 168 | 151 | 175 | 243.2 | 86.2 | 135.6 | 463.9 | 0.25 | 0.06 | 0.15 | 0.41 |
| 6 | 110 | 198 | 186 | 209 | 242.1 | 85.2 | 137.7 | 495.8 | 0.25 | 0.06 | 0.14 | 0.41 |
| 7 | 110 | 229 | 214 | 238 | 236.4 | 80.8 | 136.6 | 436.9 | 0.24 | 0.06 | 0.16 | 0.41 |
| 8 | 110 | 260 | 242 | 271 | 234.8 | 80.6 | 140.4 | 454.8 | 0.24 | 0.06 | 0.14 | 0.39 |
| 9 | 110 | 290 | 277 | 300 | 231.0 | 76.9 | 139.0 | 427.5 | 0.23 | 0.05 | 0.14 | 0.39 |
| 10 | 110 | 320 | 305 | 329 | 230.0 | 77.9 | 136.3 | 442.0 | 0.23 | 0.06 | 0.14 | 0.39 |

Table 3. Parametric Bootstrap Tests for Unbiasedness of Futures Prices

| (1) Commodity / LGM-Dairy Insurable Month | (2) Mean Prediction Error (%) | (3) Bootstrapped Prediction Error Confidence Interval (%) | (4) Bootstrap test for Unbiasedness of Futures Prices (p-values) |
|---|---|---|---|
| Class III Milk | | | |
| 1 | -0.57 | (-1.95, 1.88) | 0.562 |
| 2 | -0.61 | (-2.77, 2.76) | 0.655 |
| 3 | -0.91 | (-3.68, 3.53) | 0.627 |
| 4 | -1.26 | (-4.48, 4.44) | 0.564 |
| 5 | -1.54 | (-5.11, 4.97) | 0.536 |
| 6 | -2.11 | (-5.88, 5.61) | 0.464 |
| 7 | -2.53 | (-6.46, 6.14) | 0.431 |
| 8 | -2.93 | (-7.11, 6.69) | 0.400 |
| 9 | -3.48 | (-8.04, 7.75) | 0.387 |
| 10 | -4.95 | (-8.55, 8.29) | 0.248 |
| Corn | | | |
| 1 | -0.34 | (-2.65, 2.55) | 0.794 |
| 2 | -0.29 | (-4.04, -4.04) | 0.873 |
| 3 | -0.36 | (-4.60, 4.44) | 0.854 |
| 4 | -0.59 | (-5.40, 5.15) | 0.819 |
| 5 | -1.41 | (-7.26, 6.71) | 0.686 |
| 6 | -0.60 | (-6.86, 6.41) | 0.851 |
| 7 | -2.41 | (-8.87, 8.28) | 0.573 |
| 8 | -1.86 | (-7.37, 6.85) | 0.600 |
| 9 | -2.46 | (-10.63, 9.67) | 0.608 |
| 10 | -2.35 | (-11.50, 10.55) | 0.650 |
| Soybean Meal | | | |
| 1 | -3.07 | (-1.92, 1.87) | 0.002 |
| 2 | -4.64 | (-2.66, 2.58) | 0.001 |
| 3 | -6.28 | (-4.06, 3.90) | 0.004 |
| 4 | -7.86 | (-5.19, 4.88) | 0.004 |
| 5 | -9.86 | (-5.92, 5.67) | 0.001 |
| 6 | -10.24 | (-7.39, 6.81) | 0.007 |
| 7 | -12.61 | (-8.35, 7.62) | 0.003 |
| 8 | -13.43 | (-8.77, 7.98) | 0.003 |
| 9 | -14.97 | (-9.51, 8.80) | 0.003 |
| 10 | -15.41 | (-8.70, 8.05) | <0.001 |

Table 4. Parametric Bootstrap Tests for Unbiasedness of Implied Volatilities

| Commodity / LGM-Dairy Insurable Month | Root Mean Square Standardized Prediction Error | Bootstrapped Root Mean Square Standardized Prediction Error Confidence Interval | Bootstrap test for Unbiasedness of Implied Volatilities (p-values) |
|---|---|---|---|
| Class III Milk | | | |
| 1 | 1.23 | (0.87, 1.13) | 0.002 |
| 2 | 1.34 | (0.85, 1.15) | <0.001 |
| 3 | 1.38 | (0.83, 1.18) | <0.001 |
| 4 | 1.41 | (0.81, 1.20) | <0.001 |
| 5 | 1.42 | (0.80, 1.20) | <0.001 |
| 6 | 1.40 | (0.79, 1.22) | 0.001 |
| 7 | 1.38 | (0.78, 1.23) | 0.003 |
| 8 | 1.35 | (0.78, 1.24) | 0.005 |
| 9 | 1.34 | (0.75, 1.26) | 0.013 |
| 10 | 1.34 | (0.75, 1.26) | 0.015 |
| Corn | | | |
| 1 | 0.84 | (0.83, 1.16) | 0.075 |
| 2 | 1.02 | (0.83, 1.17) | 0.789 |
| 3 | 1.05 | (0.83, 1.18) | 0.532 |
| 4 | 0.99 | (0.82, 1.18) | 0.991 |
| 5 | 1.05 | (0.80, 1.21) | 0.519 |
| 6 | 0.98 | (0.80, 1.20) | 0.925 |
| 7 | 1.03 | (0.78, 1.23) | 0.690 |
| 8 | 1.00 | (0.77, 1.23) | 0.849 |
| 9 | 0.99 | (0.76, 1.25) | 0.935 |
| 10 | 1.00 | (0.75, 1.26) | 0.915 |
| Soybean Meal | | | |
| 1 | 1.16 | (0.87, 1.13) | 0.022 |
| 2 | 1.15 | (0.87, 1.14) | 0.025 |
| 3 | 1.19 | (0.84, 1.17) | 0.027 |
| 4 | 1.27 | (0.83, 1.18) | 0.006 |
| 5 | 1.32 | (0.81, 1.20) | 0.002 |
| 6 | 1.23 | (0.79, 1.22) | 0.033 |
| 7 | 1.31 | (0.77, 1.24) | 0.015 |
| 8 | 1.28 | (0.77, 1.24) | 0.026 |
| 9 | 1.32 | (0.77, 1.25) | 0.013 |
| 10 | 1.26 | (0.78, 1.23) | 0.031 |

**Parametric Bootstrap Tests for Futures Price and Implied Volatility Biases**
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## ONLINE APPENDIX A. – Overlapping Prediction Horizons and Test Critical Values

Futures price prediction horizons for distant months are strongly overlapping. It is interesting to examine how much extra burden this places on the evidence needed to reject the null hypothesis of no volatility bias, compared to what would be required in a sample with the same number of observations, but with non-overlapping data. In our test for volatility bias, the only two data features that influence the critical values are (i) the number of observations and (ii) the z-score correlations. Thus, any differences between critical values in our test with the1$^{st}$ nearby and our test with contracts with higher nearby index are due solely to prediction horizon overlap.

In (21), if horizons were non-overlapping, then standard normal draws $z^*_{l,k}$ would be uncorrelated. The sum of $N$ square i.i.d. standard normal deviates is distributed $\chi^2(N)$ implying that $N\overline{SSPE}^* \sim \chi^2(N)$. Absent prediction horizon overlap we would not need a bootstrap to test for volatility bias. Instead, we would obtain critical RMSSPE values by calculating directly 2.5$^{th}$ and 97.5$^{th}$ percentiles of the $\chi^2(N)$ distribution, dividing both values by the sample size *N*, then taking square roots. For example, given that we have 164 Class III milk contracts in our sample the required percentiles of the $\chi^2(164)$ are 130.43 and 201.35. Dividing by 164, and taking square roots we obtain 0.892 and 1.108. Bootstrapped critical values for the 1$^{st}$ nearby contracts should match these numbers, as those data do not have overlapping horizons. Indeed, critical RMSSPE values for 1$^{st}$ nearby Class III Milk contracts in Table C.3 are 0.89 and 1.11, extremely close to the above values.

We compare our bootstrapped critical values for more distant contracts with these numbers to gain insight on the burden overlapping prediction horizons impose on evidence needed to reject the null hypothesis of implied volatility unbiasedness. For example, for the $10^{th}$ insurable month, critical Class III values are 0.75 and 1.26 – a considerably wider confidence interval than under no-overlap situation. It would take 30 non-overlapping observations to obtain the same confidence interval. For a $10^{th}$ insurable month prices, that would be equivalent to 27 years of data, or twice as long estimation period than in our sample. Alternatively, non-overlapping $10^{th}$ nearby series available to us only has 15 observations and critical values would be 1.35 and 0.64, creating much wider confidence interval than used in our test. Therefore, using all available futures and options data can considerably increase utilized information content of small samples, even when prediction horizons are strongly overlapping.

**Parametric Bootstrap Tests for Futures Price and Implied Volatility Biases With Application to Rating Dairy Margin Insurance**

## ONLINE APPENDIX B. – Robustness Checks I: Risk-Premium in Futures Prices

In the main body of the text we find that volatility bias tests indicate soybean meal implied volatilities are downward biased. However, this test is conducted under the assumption that futures prices are unbiased. If soybean meal futures prices exhibit time varying premiums then tests for volatility biases based on (12) will be misspecified. In this appendix we test for presence of biases in implied volatilities under the assumption that futures prices are efficient and exhibit time-varying risk premium *r*, estimated using the sample average PPE as follows:

(B.1) $$r = -\overline{PPE}_j / 100$$

The above implies that $E_t\left(p_T\right) - f_t = rf_t$. If $r > 0$ then our model specification implies that risk premiums are increasing in the level of futures prices. McKenzie and Holt (2002) and Frank and Garcia (2009) develop models with time-varying risk premiums, and assert that testing for a constant risk premium may yield misleading results. In their analyses the risk premium is modeled as increasing in market volatility. Previous research has shown that in agricultural markets, higher prices are associated with higher volatility (Williams and Wright, 1991). As such, the version of our model that allows time-varying risk premiums estimated by (B.1) is consistent with earlier literature and able to easily accommodate basic characteristics of agricultural commodity markets.

Under (B.1) expected terminal log-prices are

(B.2) $$E_t\left(\ln p_{T,j}\right) = \ln f_{t,j} + \ln\left(1 - \frac{\overline{PPE}_j}{100}\right) - \frac{1}{2}\sigma_{t,j}^2\tau$$

Under the null hypothesis of unbiased implied volatilities, (B.2) is consistent with $E_t\left(P_{T,j}\right)=\left(1+r\right)f_{t,j}$. The testable expression in a price-bias-adjusted test for unbiasedness of implied volatilities is a modification of (12):

$$\text{(B.3)} \qquad \sqrt{\frac{1}{N}\sum_{l=1}^{N}\left[\frac{\ln p_{l,j}-\left(\ln f_{l,j}+\ln\left(1-\frac{\overline{PPE}_j}{100}\right)-\frac{1}{2}\sigma_{l,j}^2\tau\right)}{\sigma_{l,j}\sqrt{\tau}}\right]^2}\overset{?}{=}1$$

The bootstrapped distribution of the variance unbiasedness test statistic in (15) depends directly on the autocorrelation structure of standard normal draws $z_{l,k}$ and the sample size, but not on futures prices or implied volatilities. It follows that the test statistic will be the same whether the variance unbiasedness test imposes the assumption of unbiasedness in futures prices or a time-varying risk premium as in (B.2).

Results of our futures-bias adjusted bootstrap tests for implied volatilities unbiasedness are shown in Table B.1. In the main body of the text, the null hypothesis of no IV bias in soybean meal is rejected under the assumption of unbiased futures prices. Relaxing the price bias assumption reverses the results of the volatility bias tests. Futures bias adjusted RMSSPEs for soybean meal are not large enough for hypothesis of no IV biases to be rejected. The results for corn and Class III milk are not qualitatively changed.

Table B.1. Parametric Bootstrap Tests for Unbiasedness of Implied Volatilities using *LGM-Dairy* Data

| Commodity / LGM-Dairy Insurable Month | Root Mean Square Standardized Prediction Error (Futures Bias Adjusted) | Bootstrapped Root Mean Square Standardized Prediction Error Confidence Interval | Bootstrap test for Unbiasedness of Implied Volatilities (Futures Bias Adjusted) (p-values) |
|---|---|---|---|
| Class III Milk | | | |
| 1 | 1.23 | (0.87, 1.13) | 0.003 |
| 2 | 1.34 | (0.85, 1.15) | <0.001 |
| 3 | 1.38 | (0.83, 1.18) | <0.001 |
| 4 | 1.41 | (0.81, 1.20) | <0.001 |
| 5 | 1.42 | (0.80, 1.20) | <0.001 |
| 6 | 1.40 | (0.79, 1.22) | <0.001 |
| 7 | 1.38 | (0.78, 1.23) | 0.003 |
| 8 | 1.35 | (0.78, 1.24) | 0.007 |
| 9 | 1.34 | (0.75, 1.26) | 0.019 |
| 10 | 1.34 | (0.75, 1.26) | 0.029 |
| Corn | | | |
| 1 | 0.84 | (0.83, 1.16) | 0.069 |
| 2 | 1.02 | (0.83, 1.17) | 0.806 |
| 3 | 1.05 | (0.83, 1.18) | 0.540 |
| 4 | 0.99 | (0.82, 1.18) | 0.977 |
| 5 | 1.05 | (0.80, 1.21) | 0.562 |
| 6 | 0.98 | (0.80, 1.20) | 0.916 |
| 7 | 1.03 | (0.78, 1.23) | 0.764 |
| 8 | 1.00 | (0.77, 1.23) | 0.880 |
| 9 | 0.99 | (0.76, 1.25) | 0.966 |
| 10 | 1.00 | (0.75, 1.26) | 0.931 |
| Soybean Meal | | | |
| 1 | 1.16 | (0.87, 1.13) | 0.170 |
| 2 | 1.15 | (0.87, 1.14) | 0.390 |
| 3 | 1.19 | (0.84, 1.17) | 0.435 |
| 4 | 1.27 | (0.83, 1.18) | 0.181 |
| 5 | 1.32 | (0.81, 1.20) | 0.254 |
| 6 | 1.23 | (0.79, 1.22) | 0.680 |
| 7 | 1.31 | (0.77, 1.24) | 0.634 |
| 8 | 1.28 | (0.77, 1.24) | 0.924 |
| 9 | 1.32 | (0.77, 1.25) | 0.822 |
| 10 | 1.26 | (0.78, 1.23) | 0.741 |

**Parametric Bootstrap Tests for Futures Price and Implied Volatility Biases With Application to Rating Dairy Margin Insurance**

## ONLINE APPENDIX C. – Robustness Checks II: Analysis using *Nearby* Data

In the main body of this article we follow data collection methods as specified in the LGM-Dairy rating method. We will refer to data obtained using LGM-Dairy rating method rules as *LGM-Dairy* data. As described in the text, such approach involves three alterations to observed futures and options data. Alterations that are applied before tests are conducted:

1) Instead of using a daily settlement futures price on a particular day, expected price is calculated by taking three-day averages of daily settlement futures prices. The same procedure applies for terminal prices, and implied volatilities used in LGM-Dairy premium determination are similarly obtained through two-day averaging.
2) Missing observations for implied volatilities at distant months are imputed using observed implied volatilities for contracts with shorter time-to-maturity.
3) While corn and soybean meal options expire several weeks before their underlying futures contracts, for LGM-Dairy premium determination purposes, time-to-maturity is based on futures, rather than options expiration date.

Our tests reveal the presence of bias in soybean meal futures prices and/or implied volatilities, and Class III Milk implied volatilities. A question may be raised if such results are due to the biases in futures and options markets, or the procedure LGM-Dairy rating method uses to modify futures and options data, impute missing values and adjust time-to-maturity length. To check for robustness of our results, and to separately identify any potential effect of LGM-Dairy data rules, we conduct separate parametric bootstrap tests using unaltered futures and options data.

In particular, for each contract, we collect data on the first day when that contract obtained $j$ nearby status, with $j = 1, ..., 12$ for milk, $j = 1, ..., 5$ for corn and $j = 1, ..., 8$ for soybean meal. We than proceed with running parametric bootstrap tests for each commodity and nearby index separately. We refer to data obtained in such a fashion as *Nearby* data. Descriptive statistics for *Nearby* data are presented in Table C.1.

*Results of the parametric bootstrap tests using Nearby data*

The results of our parametric bootstrap tests for unbiasedness of futures prices using *Nearby* data are summarized in Table C.2. Tests for biases in implied volatilities are given in Table C.3. Missing data prevents testing for 6$^{th}$ through 8$^{th}$ nearby soybean meal, as well as for 11$^{th}$ and 12$^{th}$ nearby Class III milk. We find that results are not qualitatively different than those obtained using the *LGM-Dairy* data and presented in Tables 3, 4 and B.1. We conclude that biases uncovered by the parametric bootstrap tests are not due to modifications to futures and options data required by the LGM-Dairy rating method, but originate in futures and option markets instead.

Table C.1. Descriptive Statistics for Data Used in Parametric Bootstrap – *Nearby* Data

| Commodity/ Nearby | Num Obs | Time To Maturity (Calendar Days) | | | Futures ($) | | | | Implied Volatility | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Avg | Min | Max | Avg | S.D. | Min | Max | Mean | S.D. | Min | Max |
| Class III Milk | | | | | | | | | | | | |
| 1 | 164 | 31 | 27 | 36 | 14.10 | 3.32 | 8.50 | 21.50 | 0.10 | 0.05 | 0.02 | 0.26 |
| 2 | 164 | 61 | 55 | 65 | 14.04 | 3.07 | 8.93 | 21.34 | 0.19 | 0.05 | 0.07 | 0.32 |
| 3 | 164 | 91 | 84 | 98 | 14.04 | 2.81 | 9.45 | 20.55 | 0.21 | 0.04 | 0.10 | 0.34 |
| 4 | 164 | 122 | 118 | 127 | 14.04 | 2.63 | 9.60 | 20.56 | 0.21 | 0.04 | 0.10 | 0.34 |
| 5 | 164 | 152 | 147 | 156 | 14.01 | 2.46 | 9.65 | 20.16 | 0.20 | 0.04 | 0.10 | 0.31 |
| 6 | 164 | 183 | 175 | 190 | 14.00 | 2.34 | 9.80 | 20.00 | 0.20 | 0.03 | 0.11 | 0.29 |
| 7 | 164 | 213 | 208 | 219 | 13.93 | 2.25 | 9.85 | 19.95 | 0.20 | 0.03 | 0.11 | 0.30 |
| 8 | 163 | 244 | 237 | 250 | 13.89 | 2.17 | 9.85 | 19.65 | 0.20 | 0.03 | 0.11 | 0.30 |
| 9 | 161 | 274 | 271 | 280 | 13.83 | 2.08 | 10.50 | 19.46 | 0.19 | 0.03 | 0.11 | 0.31 |
| 10 | 157 | 305 | 299 | 336 | 13.76 | 2.05 | 10.65 | 19.50 | 0.19 | 0.03 | 0.11 | 0.29 |
| 11 | 146 | 335 | 328 | 343 | 13.77 | 2.04 | 10.71 | 19.58 | 0.19 | 0.03 | 0.08 | 0.31 |
| 12 | 127 | 365 | 362 | 372 | 14.01 | 1.99 | 11.00 | 19.70 | 0.19 | 0.03 | 0.11 | 0.29 |
| Corn | | | | | | | | | | | | |
| 1 | 69 | 73 | 56 | 94 | 3.68 | 1.81 | 1.90 | 8.09 | 0.30 | 0.08 | 0.16 | 0.46 |
| 2 | 69 | 146 | 119 | 182 | 3.67 | 1.74 | 2.02 | 8.09 | 0.29 | 0.08 | 0.16 | 0.47 |
| 3 | 69 | 219 | 182 | 245 | 3.63 | 1.63 | 2.09 | 8.01 | 0.28 | 0.07 | 0.17 | 0.44 |
| 4 | 69 | 292 | 266 | 309 | 3.58 | 1.50 | 2.17 | 7.84 | 0.27 | 0.06 | 0.18 | 0.41 |
| 5 | 67 | 365 | 357 | 371 | 3.56 | 1.45 | 2.23 | 7.79 | 0.27 | 0.06 | 0.19 | 0.39 |
| Soybean Meal | | | | | | | | | | | | |
| 1 | 110 | 46 | 21 | 64 | 250.2 | 93.4 | 143.9 | 526.9 | 0.27 | 0.07 | 0.16 | 0.46 |
| 2 | 110 | 92 | 56 | 126 | 245.6 | 90.8 | 143.1 | 522.8 | 0.26 | 0.07 | 0.16 | 0.45 |
| 3 | 110 | 137 | 91 | 189 | 240.9 | 87.6 | 142.7 | 514.7 | 0.25 | 0.06 | 0.16 | 0.45 |
| 4 | 109 | 183 | 147 | 224 | 236.4 | 83.7 | 142.7 | 480.7 | 0.24 | 0.06 | 0.16 | 0.44 |
| 5 | 109 | 228 | 175 | 273 | 231.6 | 78.9 | 136.0 | 441.7 | 0.24 | 0.06 | 0.15 | 0.42 |
| 6 | 99 | 273 | 238 | 308 | 227.2 | 74.5 | 143.8 | 398.2 | 0.23 | 0.06 | 0.14 | 0.41 |
| 7 | 79 | 320 | 300 | 337 | 223.7 | 72.0 | 136.5 | 385.7 | 0.23 | 0.05 | 0.15 | 0.37 |
| 8 | 58 | 365 | 361 | 371 | 220.8 | 70.2 | 138.5 | 393.0 | 0.22 | 0.05 | 0.14 | 0.36 |

Table C.2. Parametric Bootstrap Tests for Unbiasedness of Futures Prices Using *Nearby* Data

| (1) Commodity / LGM-Dairy Insurable Month | (2) Mean Prediction Error (%) | (3) Bootstrapped Prediction Error Confidence Interval (%) | (4) Bootstrap test for Unbiasedness of Futures Prices (p-values) |
|---|---|---|---|
| Class III Milk | | | |
| 1 | -0.38 | (-0.51, 0.49) | 0.134 |
| 2 | -0.52 | (-1.54, 1.53) | 0.499 |
| 3 | -0.56 | (-2.51, 2.42) | 0.656 |
| 4 | -0.79 | (-3.31, 3.32) | 0.626 |
| 5 | -1.10 | (-4.14, 4.04) | 0.584 |
| 6 | -1.42 | (-4.85, 4.65) | 0.550 |
| 7 | -1.99 | (-5.55, 5.31) | 0.471 |
| 8 | -2.40 | (-6.34, 5.99) | 0.439 |
| 9 | -2.85 | (-6.89, 6.57) | 0.410 |
| 10 | -3.43 | (-7.98, 7.35) | 0.383 |
| 11 | N/A | N/A | N/A |
| 12 | N/A | N/A | N/A |
| Corn | | | |
| 1 | -0.02 | ( -3.28, 3.10) | 0.967 |
| 2 | -0.70 | ( -6.44, 5.99) | 0.806 |
| 3 | -1.45 | ( -9.61, 8.81) | 0.737 |
| 4 | -2.14 | (-12.32, 11.09) | 0.690 |
| 5 | -2.86 | (-15.33, 13.46) | 0.674 |
| Soybean Meal | | | |
| 1 | -2.40 | (-1.80, 1.79) | 0.009 |
| 2 | -4.68 | (-3.56, 3.40) | 0.010 |
| 3 | -7.03 | (-5.06, 4.93) | 0.008 |
| 4 | -9.04 | (-6.77, 6.34) | 0.009 |
| 5 | -10.82 | (-8.70, 7.44) | 0.010 |
| 6 | N/A | N/A | N/A |
| 7 | N/A | N/A | N/A |
| 8 | N/A | N/A | N/A |

Table C.3. Parametric Bootstrap Tests for Unbiasedness of Implied Volatilities using *Nearby* Data

| Commodity / LGM-Dairy Insurable Month | Root Mean Square Standardized Prediction Error | Root Mean Square Standardized Prediction Error (Futures Bias Adjusted) | Bootstrapped Root Mean Square Standardized Prediction Error Confidence Interval | Bootstrap test for Unbiasedness of Implied Volatilities (p-values) | Bootstrap test for Unbiasedness of Implied Volatilities (Futures Bias Adjusted) (p-values) |
|---|---|---|---|---|---|
| Class III Milk | | | | | |
| 1 | 0.74 | 0.70 | (0.89, 1.11) | <0.001 | <0.001 |
| 2 | 1.17 | 1.16 | (0.88, 1.12) | 0.005 | 0.009 |
| 3 | 1.28 | 1.28 | (0.86, 1.14) | <0.001 | <0.001 |
| 4 | 1.37 | 1.37 | (0.84, 1.16) | <0.001 | <0.001 |
| 5 | 1.39 | 1.39 | (0.82, 1.18) | <0.001 | <0.001 |
| 6 | 1.42 | 1.42 | (0.81, 1.20) | <0.001 | <0.001 |
| 7 | 1.39 | 1.39 | (0.80, 1.21) | <0.001 | <0.001 |
| 8 | 1.36 | 1.36 | (0.79, 1.22) | 0.003 | 0.004 |
| 9 | 1.35 | 1.33 | (0.78, 1.24) | 0.005 | 0.006 |
| 10 | 1.33 | 1.30 | (0.77, 1.25) | 0.014 | 0.024 |
| 11 | N/A | N/A | N/A | N/A | N/A |
| 12 | N/A | N/A | N/A | N/A | N/A |
| Corn | | | | | |
| 1 | 1.08 | 1.08 | (0.83, 1.17) | 0.307 | 0.306 |
| 2 | 1.15 | 1.15 | (0.80, 1.20) | 0.132 | 0.133 |
| 3 | 1.11 | 1.11 | (0.76, 1.25) | 0.329 | 0.329 |
| 4 | 1.06 | 1.06 | (0.75, 1.27) | 0.591 | 0.593 |
| 5 | 1.03 | 1.02 | (0.72, 1.31) | 0.739 | 0.767 |
| Soybean Meal | | | | | |
| 1 | 1.09 | 1.04 | (0.87, 1.13) | 0.176 | 0.509 |
| 2 | 1.15 | 1.06 | (0.84, 1.16) | 0.064 | 0.424 |
| 3 | 1.26 | 1.13 | (0.81, 1.19) | 0.011 | 0.178 |
| 4 | 1.28 | 1.11 | (0.79, 1.22) | 0.012 | 0.292 |
| 5 | 1.26 | 1.05 | (0.78, 1.24) | 0.034 | 0.614 |
| 6 | N/A | N/A | N/A | N/A | N/A |
| 7 | N/A | N/A | N/A | N/A | N/A |
| 8 | N/A | N/A | N/A | N/A | N/A |

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## ONLINE APPENDIX D. – Straddle Analysis of Biases in Class III Milk Options

From the magnitude of Class III Milk RMSSPEs in Table 4 it is not clear as to whether these results are also economically important. To examine the issue further we create a trading strategy that would generate zero profits if implied volatilities are unbiased, but would yield positive profits if implied volatilities are too low relative to realized volatility. The trading program is executed for each $j^{th}$ nearby contract separately and is based on creating a long straddle position, i.e., buying one at-the-money put and one call option at the time when a contract first gains $j^{th}$ nearby status, and keeping both options until expiration.

To make the trading exercise more realistic, we examine how returns to trading vary with different magnitudes of slippage, defined as the difference between the option premiums actually paid and the reported daily settlement premium. We assume that slippage can be expressed as proportional to implied volatility. In particular, we examine four levels of slippage, defined as surcharge over settlement option premiums equivalent to increase in implied volatility from one to four percentage points. In personal communication with dairy traders at the CME we have established that the average difference between option ask and settlement prices corresponds to approximately two percentage points increase in implied volatility.

Results of the long straddle trading strategies in Class III milk options are presented in Table D.1. For the $3^{\text{nd}}$ and higher nearby index trading strategies generate positive returns at slippage level equivalent to two percentage point over settlement implied volatility. The highest returns are obtained for trading program for the $6^{\text{th}}$ and $7^{\text{th}}$ nearby contracts, i.e., 183-213 calendar days to maturity. In particular, for the 6th nearby contract, even after accounting for typical slippage, returns over the past 13 years average 27%.

Given the LGM-Dairy ratemaking rules, the 1st insurable month in Table 4 corresponds to the 3rd nearby index, 2nd insurable month corresponds to the 4th nearby index, etc. The results from our trading exercise not only corroborate parametric bootstrap results, but suggest that returns on strategies exploiting apparent volatility bias in Class III options are considerably high.

Table D.1. Profitability of Long Straddle Strategies in Class III Options Markets: 2000-2012

| | Nearby Index | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1st | 2nd | 3rd | 4th | 5th | 6th | 7th | 8th | 9th | 10th | 11th | 12th |
| Average Long Straddle Cost / Slippage | | | | | | | | | | | | |
| No Slippage | $0.32 | $0.87 | $1.17 | $1.35 | $1.51 | $1.63 | $1.73 | $1.81 | $1.89 | $1.97 | $2.08 | $2.17 |
| 1% over settlement IV | $0.36 | $0.92 | $1.22 | $1.42 | $1.58 | $1.70 | $1.81 | $1.90 | $1.99 | $2.07 | $2.18 | $2.28 |
| 2% over settlement IV | $0.39 | $0.96 | $1.28 | $1.48 | $1.65 | $1.78 | $1.90 | $1.99 | $2.08 | $2.17 | $2.28 | $2.39 |
| 3% over settlement IV | $0.42 | $1.01 | $1.33 | $1.55 | $1.72 | $1.86 | $1.98 | $2.08 | $2.17 | $2.26 | $2.39 | $2.50 |
| 4% over settlement IV | $0.45 | $1.05 | $1.39 | $1.61 | $1.79 | $1.94 | $2.06 | $2.17 | $2.27 | $2.36 | $2.49 | $2.61 |
| Average Long Straddle Payoff | $0.17 | $0.83 | $1.25 | $1.59 | $1.88 | $2.11 | $2.23 | $2.31 | $2.34 | $2.42 | $2.57 | $2.79 |
| Long Straddle Return On Investment / Slippage | | | | | | | | | | | | |
| No slippage | -41% | 3% | 16% | 27% | 34% | 40% | 38% | 35% | 31% | 29% | 34% | 41% |
| 1% over settlement IV | -48% | -3% | 10% | 21% | 27% | 33% | 31% | 29% | 24% | 23% | 27% | 34% |
| 2% over settlement IV | -53% | -9% | 5% | 15% | 21% | 27% | 25% | 23% | 19% | 17% | 21% | 27% |
| 3% over settlement IV | -58% | -14% | 0% | 10% | 16% | 21% | 19% | 17% | 13% | 12% | 15% | 21% |
| 4% over settlement IV | -61% | -18% | -5% | 5% | 11% | 16% | 14% | 12% | 8% | 7% | 10% | 15% |

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## ONLINE APPENDIX E. – Can Rare Events explain Apparent Downward Bias in Class III Milk Implied Volatilities?

One explanation for the apparent bias in Class III options could be that our relatively short sample contains events that occur much less frequently than once in 13 years. One such extreme event occurred in the spring of 2004 when rapid unanticipated increase in milk prices reflected a sudden 50% cutback in supply of Posilac, an artificial bovine growth hormone used to boost milk yields.[1] Yet another obvious candidate is the Great Recession of 2008-2009. At that time, Class III milk prices collapsed from an average of $15.95/cwt in the last quarter of 2008 to $10.19 in the first half of 2009.

To examine the robustness of our results with respect to outliers, we conducted the parametric bootstrap test after removing contracts from March through June of 2004 and the first six months of 2009. The results are presented in Table E.1. We find that the null hypothesis of unbiased implied volatilities is no longer rejected for the 2$^{nd}$ nor 3$^{rd}$ nearby contract. While the null is still rejected at 95% confidence for 4$^{th}$ through 8$^{th}$ nearby contracts, it is rejected only at 90% for 9$^{th}$ nearby, and it is not rejected for 10$^{th}$ nearby contracts. Table E.2. presents the return to the long straddle trading program. After excluding both spring 2004 and the first half of 2009 from our sample we find that the average return for the remaining trades in the sample was 11% for the 6$^{th}$ nearby contract (at 2% slippage), though average returns were -9% and 1% respectively for 3$^{rd}$ and the 4$^{th}$ nearby. Looking further for short periods with exceedingly high

[1] Other factors contributing to spring 2004 price spike include the severe western drought, impacting reproduction during the summer of 2003, and closing of the border with Canada to the importation of replacement heifers as a result of a BSE scare. The full import of these factors was not realized until the spring of 2004.

returns, we find that for the 6$^{th}$ nearby contract, 74% of the cumulative profit over 164 trades of our trading program is attributable to only 8 trades: April-June 2004, June-July 2007 and January-March 2009, and excluding all these periods would reduce average return to 9%.

Results of statistical tests and trading programs conducted with the truncated sample indicate that while presence of rare events may have contributed to high observed returns to long straddle positions, the potential overrepresentation of rare events does not fully explain the downward bias in Class III milk implied volatilities, especially for prediction horizons from 120 to 220 calendar days to maturity. Neither it is clear that high returns in stated periods can indeed be attributed to events that are extremely infrequent. In particular, the run-up in milk prices in 2007 was fueled by the strong export demand for U.S. dairy products. Similarly, the milk price collapse in the first half of 2009 is at least partially attributable to mild U.S. winter weather resulting in increased milk yield, the strengthening of the U.S. dollar that made dairy exports less competitive, and strong recovery in milk production in Oceania after two years of depressed productivity due to droughts.

Given highly inelastic short-run demand for milk, even moderate changes in supply can induce severe price corrections. Historically, large unpredictable oscillations in milk production in Oceania have been a rule, rather than the exception. El Nino/La Nina-Southern Oscillation has traditionally impacted pasture-based dairy systems in New Zealand quite substantially. In 12 of the past 40 years, New Zealand’s annual milk yield growth deviated from the average growth rate by more than 7%. Such movements are enough to induce major shocks to world dairy product prices given the importance New Zealand is with respect to world dairy trade. Traditionally, U.S. milk prices have been decoupled from world prices due to high support prices and import tariffs. Over the last ten years, the U.S. has become a major world player with more than 13% of total U.S. milk solids being exported in 2012 (USDEC 2013). As such, large price swings of 2007 and 2009 could be harbingers of new and more volatile price regime, rather than over-represented rare events.

Table E.1. Parametric Bootstrap Tests for Unbiasedness of Implied Volatilities – Rare Events Excluded

| Commodity / LGM-Dairy Insurable Month | Root Mean Square Standardized Prediction Error | Bootstrapped Root Mean Square Standardized Prediction Error Confidence Interval | Bootstrap test for Unbiasedness of Implied Volatilities (Rare Events (p-values) |
|---|---|---|---|
| Class III Milk | | | |
| 1 | 0.70 | (0.89, 1.11) | <0.001 |
| 2 | 0.94 | (0.88, 1.12) | 0.346 |
| 3 | 1.12 | (0.86, 1.14) | 0.092 |
| 4 | 1.26 | (0.84, 1.16) | 0.002 |
| 5 | 1.28 | (0.82, 1.18) | 0.003 |
| 6 | 1.32 | (0.81, 1.19) | 0.002 |
| 7 | 1.27 | (0.80, 1.21) | 0.011 |
| 8 | 1.24 | (0.79, 1.22) | 0.036 |
| 9 | 1.22 | (0.78, 1.24) | 0.063 |
| 10 | 1.20 | (0.77, 1.25) | 0.112 |
| 11 | N/A | N/A | N/A |
| 12 | N/A | N/A | N/A |

Table E.2. Profitability of Long Straddle Strategies in Class III Options Markets: 2000-2013. Rare Events Excluded.

| | Nearby Index | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1st | 2nd | 3rd | 4th | 5th | 6th | 7th | 8th | 9th | 10th | 11th | 12th |
| Average Long Straddle Cost / Slippage | | | | | | | | | | | | |
| No Slippage | $0.32 | $0.87 | $1.17 | $1.37 | $1.51 | $1.63 | $1.72 | $1.79 | $1.87 | $1.94 | $2.05 | $2.16 |
| 1% over settlement IV | $0.35 | $0.92 | $1.23 | $1.43 | $1.59 | $1.71 | $1.80 | $1.88 | $1.96 | $2.04 | $2.15 | $2.26 |
| 2% over settlement IV | $0.39 | $0.96 | $1.28 | $1.50 | $1.66 | $1.78 | $1.89 | $1.97 | $2.05 | $2.13 | $2.25 | $2.37 |
| 3% over settlement IV | $0.42 | $1.01 | $1.34 | $1.56 | $1.73 | $1.86 | $1.97 | $2.06 | $2.15 | $2.23 | $2.36 | $2.48 |
| 4% over settlement IV | $0.45 | $1.06 | $1.40 | $1.62 | $1.80 | $1.94 | $2.05 | $2.14 | $2.24 | $2.33 | $2.46 | $2.59 |
| Average Long Straddle Payoff | $0.13 | $0.74 | $1.11 | $1.41 | $1.65 | $1.84 | $1.91 | $1.95 | $1.96 | $2.01 | $2.12 | $2.30 |
| Long Straddle Return On Investment / Slippage | | | | | | | | | | | | |
| No slippage | -57% | -11% | 1% | 11% | 17% | 22% | 20% | 18% | 14% | 12% | 14% | 15% |
| 1% over settlement IV | -62% | -16% | -4% | 5% | 11% | 16% | 14% | 12% | 8% | 6% | 8% | 9% |
| 2% over settlement IV | -65% | -20% | -9% | 1% | 6% | 11% | 9% | 7% | 3% | 1% | 3% | 4% |
| 3% over settlement IV | -68% | -24% | -13% | -4% | 1% | 6% | 4% | 2% | -1% | -3% | -2% | -1% |
| 4% over settlement IV | -71% | -28% | -17% | -8% | -3% | 1% | 0% | -2% | -6% | -8% | -6% | -5% |

Note: March-June 2004 and January-June 2009 contracts excluded from the trading analysis.

**Parametric Bootstrap Tests for Futures Price and Implied Volatility Biases With Application to Rating Dairy Margin Insurance**

**ONLINE APPENDIX F. – Impact of Biases on LGM-Dairy Premiums**

In this Appendix we review the results of Monte Carlo experiments designed to quantify the consequences of uncovered futures price and implied volatility biases for LGM-Dairy premiums. In particular, downward biased soybean meal futures prices, as well as downward biased Class III milk option premiums would be expected to result in downward biased LGM-Dairy premiums. To facilitate our analysis of the impact of price and volatility biases on LGM-Premium calculations, we define 24 representative contract configurations. Each contract is based on monthly milk marketings of 9,000 cwt, an amount expected from a farm with 500 milking cows with 21,600 lbs annual per cow milk yield. These contracts differ in three dimensions:

(i) *Amount of feed declared per cwt. of milk*. We consider three feeding regimes: ***Minimum*** allowable feed use and ***Maximum*** feed use are representative of two distinct production systems: farms that grow all their feed versus dry-lot farming systems where all feed are purchased on the market. In addition, we examine the scenario where the LGM-Dairy default feed amounts per cwt of milk are utilized (RMA 2005)

(ii) *Chosen deductible level*. We consider an insurance under high risk aversion ($0.00/cwt deductible) and usage of LGM-Dairy as a catastrophe insurance that does not cover shallow losses ($1.10 deductible).

(iii) *Risk management strategy*. Four different risk management strategies are considered in our analysis. In each strategy, we assume the representative farm operator purchases an LGM-Dairy contract regularly every month. The four alternative contract designs are:

1) ***Flat-10***: 1/10 of expected milk marketings are insured for each of the ten insurable months.
2) ***Up Front***: 1/3 of expected milk marketings are insured for the 1st, 2nd and 3rd insurable months.
3) ***Middle of the Road***: 1/3 of expected milk marketings are insured for the 4th, 5th and 6th insurable months.
4) ***Looking Ahead***: 1/3 of expected milk marketings are insured for the 8th, 9th, and 10th insurable months.

We assume that LGM-Dairy contracts were purchased monthly from January 2010 through December 2012. Regardless of the strategy adopted, eventually 100% of the expected milk marketings will be insured under LGM-Dairy contracts.

To examine the impact of soybean meal futures price bias, we assume that the true relationship between futures and expected terminal prices is:

$$\left(1-\frac{\overline{PPE_i}}{100}\right) f_{t,i} = E_t\left(p_{T,i}\right) \qquad \text{(F.1)}$$

where $i = 1,\ldots,10$ represents the LGM-Dairy insurable month index. In the scenario examined here, downward biases for soybean meal prices are set at an observed sample average PPEs, calculated separately for each insurable month index, as shown in the second column in Table D.1. Futures prices used in LGM-Dairy premium determination are adjusted using the following calibration coefficients

$$c_i^{SBM} = 1 - \frac{\overline{PPE}_i}{100} \tag{F.2}$$

There are two ways to re-design the LGM-Dairy rating method to account for futures prices biases. First, the gross margin guarantee (GMG) can be altered to be based on bias-adjusted expected prices. Alternatively, GMG can be based on observed futures prices, as is currently the case. If GMG is not altered, then we must add to the premium the full difference between the GMG calculated using the futures prices, and GMG calculated using the bias-adjusted expected prices. We examine the effect on premiums under both approaches.

In the next exercise, we examine the effect of potential volatility biases in Class III milk prices on LGM-Dairy premiums. Sample-based root mean SSPE is a function of futures prices $f_{t,i}$, terminal prices $p_{T,i}$, and implied volatility coefficients $\sigma_{t,i}$, as given in the equation (11). We modify each observed implied volatility by a calibrating coefficient $c$ so that $\sigma_{t,i}^c = c\sigma_{t,i}$. Holding $f_{t,i}$, $p_{T,i}$ and $\sigma_{t,i}$ constant, RMSSPE can be construed as a function of $c$ only, with

$$\frac{\partial RMSSPE}{\partial c} < 0 \tag{F.3}$$

We develop an algorithm that finds the smallest $\tilde{c}$ still sufficiently high that parametric bootstrap test no longer rejects the null hypothesis of no volatility biases:

$$RMSSPE\left(\tilde{c}\right) = RMSSPE_{i,1-\alpha/2}^{*} \tag{F.4}$$

In words, the calibrated sample-based RMSSPE matches the 97.5$^{th}$ percentile of the bootstrapped distribution of RMSSPEs. When calculating LGM-Dairy premiums, we replace each Class III milk implied volatility $\sigma_{t,i}$ with its calibrated counterpart $\tilde{c}\sigma_{t,i}$.

Given that a portion of the volatility bias may be explained by overrepresentation of rare events, we examine how sensitive are LGM-Dairy premium corrections to excluding the rare events from the sample. We find the calibrating coefficient in the same fashion as in equation (F.4). To be conservative, in this scenario we find $\tilde{c}$ that matches calibrated RMSSPE from the truncated sample to 95$^{th}$, rather than 97.5$^{th}$ percentile of the bootstrapped distribution. As such, this scenario would be employed if LGM-Dairy contract designers judged the observed historic milk volatility biases as emanating predominantly from market anomalies that are not expected to be repeated. Table F.1. contains the calibration coefficients.

[Insert Table F.1 about Here]

Table F.2. is used to summarize the results of the above simulations. Columns (1) through (3) identify the insurance policy profiles in terms of risk management strategy chosen, level of deductible, and amount of declared feed. In column (4) we provide average monthly insurance premiums using the current LGM-Dairy rating methodology. Columns (5) and (7) present the premiums under the assumption of downward bias in soybean meal futures prices. The method used in column (5) utilizes gross margin guarantee (GMG) based on bias-adjusted expected prices. In contrast, column (7) continues the current practice of basing GMG on three-day averages of futures prices. We find that even for the policies that use maximum feed amounts and buy insurance for the distant months in which bias is most pronounced, fully accounting for the bias in the rating method would render insurance policy premiums less than 3% higher, as the brunt of the impact is born by the reduction in GMG. In contrast, partial accounting for soybean meal futures bias whereby GMG being based on unadjusted futures prices would significantly increase policy premiums.

[Insert Table F.2 About Here]

Results of the simulation in which Class III milk implied volatility biases are accounted for in the rating method are presented in columns (9) and (11). Column (9) presents results based on full sample data. However, if we subscribe to the rare-events hypothesis described in the previous section, we should adjust implied volatilities according to method described in equation (F.4), but excluding the periods March-June 2004 and January-June 2009. Those results are presented in column (11). Results from method with full sample data, presented in column (9), reveal that LGM-Dairy premiums are very sensitive to volatility biases, and inflating the volatility coefficients to account for these biases increased premiums up to 34%. The largest increases were obtained for contracts utilizing high deductible, and up-front and middle-of-the-road risk management strategies. Excluding rare events from the calibration exercise reduces the LGM-Dairy premium increases considerably. The highest increase in this method is 7.7% for middle-of-the-road strategy with minimum declared feed and $1.10 deductible level.

Table F.1. Calibration Coefficients Used in LGM-Dairy Rating Method Sensitivity Analysis

| Insurable Month | Class III Milk Implied Volatility | | Soybean Meal Futures Prices |
|---|---|---|---|
| | Full Data | No Rare Events | |
| 1 | 1.076 | 1.000 | 1.031 |
| 2 | 1.162 | 1.000 | 1.046 |
| 3 | 1.175 | 1.012 | 1.063 |
| 4 | 1.179 | 1.026 | 1.079 |
| 5 | 1.183 | 1.050 | 1.099 |
| 6 | 1.152 | 1.031 | 1.102 |
| 7 | 1.127 | 1.012 | 1.126 |
| 8 | 1.097 | 1.000 | 1.134 |
| 9 | 1.063 | 1.000 | 1.150 |
| 10 | 1.061 | 1.000 | 1.154 |

Note: Class III Milk calibration coefficients are calculated using equation (F.4) and modify implied volatility coefficients via $\sigma_{t,i}^{c} = c\sigma_{t,i}$ . Soybean meal calibration coefficients are calculated using equation (F.1) and modify futures prices via $f_{t,i}^{c} = c_{i}^{SBM} f_{t,i}$

Table F.2. Sensitivity Analysis of Changes in 2010-2012 LGM-Dairy Premiums under Biased Futures Prices and Implied Volatilities

| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Biased Soybean Meal Futures Prices | | | | Biased Class III Milk Implied Volatilities | | | |
| Strategy | Deductible Level ($/cwt) ($/cwt) | Feed Declared | RMA Rating Method ($) | Gross Margin Guarantee Altered ($) | (%) | Gross Margin Guarantee Not Altered ($) | (%) | Bias Estimated Using Full Sample ($) | (%) | Bias Estimated Excluding Rare Events ($) | (%) |
| Flat-10 | $0.00 | Minimum | 7,120 | 7,122 | 0.0% | 7,324 | 2.9% | 7,990 | 12.2% | 7,216 | 1.4% |
| | | Default | 7,459 | 7,481 | 0.3% | 8,435 | 13.1% | 8,294 | 11.2% | 7,551 | 1.2% |
| | | Maximum | 9,944 | 10,099 | 1.6% | 13,243 | 33.2% | 10,572 | 6.3% | 10,011 | 0.7% |
| | $1.10 | Minimum | 2,975 | 2,977 | 0.1% | 3,180 | 6.9% | 3,687 | 23.9% | 3,053 | 2.6% |
| | | Default | 3,315 | 3,335 | 0.6% | 4,292 | 29.4% | 4,004 | 20.8% | 3,390 | 2.3% |
| | | Maximum | 5,749 | 5,893 | 2.5% | 9,048 | 57.4% | 6,285 | 9.3% | 5,807 | 1.0% |
| Up Front | $0.00 | Minimum | 5,890 | 5,891 | 0.0% | 5,984 | 1.6% | 6,738 | 14.4% | 5,918 | 0.5% |
| | | Default | 6,106 | 6,118 | 0.2% | 6,557 | 7.4% | 6,928 | 13.5% | 6,134 | 0.4% |
| | | Maximum | 7,755 | 7,819 | 0.8% | 9,277 | 19.6% | 8,414 | 8.5% | 7,776 | 0.3% |
| | $1.10 | Minimum | 2,028 | 2,029 | 0.0% | 2,123 | 4.6% | 2,676 | 31.9% | 2,049 | 1.0% |
| | | Default | 2,224 | 2,231 | 0.3% | 2,674 | 20.2% | 2,854 | 28.3% | 2,244 | 0.9% |
| | | Maximum | 3,743 | 3,794 | 1.4% | 5,265 | 40.7% | 4,271 | 14.1% | 3,760 | 0.4% |
| Middle of the Road | $0.00 | Minimum | 8,437 | 8,439 | 0.0% | 8,639 | 2.4% | 9,847 | 16.7% | 8,732 | 3.5% |
| | | Default | 8,800 | 8,822 | 0.2% | 9,765 | 11.0% | 10,156 | 15.4% | 9,083 | 3.2% |
| | | Maximum | 11,485 | 11,634 | 1.3% | 14,747 | 28.4% | 12,554 | 9.3% | 11,703 | 1.9% |
| | $1.10 | Minimum | 4,071 | 4,072 | 0.0% | 4,273 | 5.0% | 5,294 | 30.1% | 4,323 | 6.2% |
| | | Default | 4,457 | 4,477 | 0.4% | 5,422 | 21.6% | 5,636 | 26.4% | 4,700 | 5.4% |
| | | Maximum | 7,158 | 7,299 | 2.0% | 10,419 | 45.6% | 8,086 | 13.0% | 7,346 | 2.6% |
| Looking Ahead | $0.00 | Minimum | 10,493 | 10,495 | 0.0% | 10,792 | 2.9% | 11,232 | 7.0% | 10,493 | 0.0% |
| | | Default | 10,927 | 10,959 | 0.3% | 12,357 | 13.1% | 11,638 | 6.5% | 10,927 | 0.0% |
| | | Maximum | 14,167 | 14,415 | 1.7% | 19,001 | 34.1% | 14,718 | 3.9% | 14,167 | 0.0% |
| | $1.10 | Minimum | 5,887 | 5,889 | 0.0% | 6,186 | 5.1% | 6,550 | 11.3% | 5,887 | 0.0% |
| | | Default | 6,347 | 6,380 | 0.5% | 7,777 | 22.5% | 6,982 | 10.0% | 6,347 | 0.0% |
| | | Maximum | 9,695 | 9,942 | 2.5% | 14,529 | 49.9% | 10,188 | 5.1% | 9,695 | 0.0% |